



OPEN Global land cover maps do not reveal mining pressures to biodiversity

Laura J. Sonter^{1,2,3}✉, Ilyas Nursamsi^{2,3}, Leon Bennun⁴, Jamie Graham¹, Victor Maus^{5,6}, Hugo Rainey¹, Malcolm Starkey¹, Joseph A. Turner¹, James E. M. Watson^{2,3} & Graham W. Prescott¹

Global land cover maps are key inputs into the biodiversity metrics used by the private sector to align their performance with conservation goals and targets. These maps utilize classification systems depicting combinations of 'natural' (vegetation, water bodies) and 'anthropogenic' (agriculture and built-up land) cover types, but often miss intensive pressures on biodiversity, such as mining. Here, we reveal that more than half (56–77%) the global land area disturbed by mining is classified by land cover maps as 'natural', suggesting metrics based on these maps likely overestimate the current state of biodiversity and underestimate opportunities to improve it. The proportion of mining land classified as natural varies by continent (e.g. 46% in Europe; 69% in Australia), further biasing initial screening efforts to identify where to mitigate negative impacts of mining. Improving the spatial and temporal resolution of land cover maps and better integrating cumulative impact mapping into biodiversity metrics, rather than relying on land cover maps which are not designed to capture land use pressures, is necessary. Current biodiversity metrics that utilise global land cover maps must be supplemented and validated with local data on ecosystem extent and condition, as well as species abundance and extinction risk, through targeted field studies, particularly in regions with large mining sectors and significant biodiversity value.

Achieving global goals for nature requires reducing land use pressures—the leading cause of biodiversity decline across the terrestrial biosphere^{1,2}. Engagement by the public and private sectors is essential for meaningful progress towards these goals for nature³, and several initiatives are emerging to support such action. For example, the 196 signatory nations to the Kunming-Montreal Global Biodiversity Framework have committed to, by 2030, protect 30% of land areas from further loss and degradation, restore 30% of all currently degraded ecosystems, and reduce loss of highly intact ecosystems to zero⁴. Similarly, companies and financial institutions are committing to mitigate biodiversity losses caused by their direct operations and value chains^{5,6} by prioritizing conservation actions to locations where nature-related risks and opportunities are largest⁷. If implemented comprehensively – across nations and sectors – these public and private actions should yield significant conservation benefits⁸; however, informing actions and monitoring progress towards these goals requires a suite of global data, indicators and metrics for which limitations and uncertainties are not yet well understood^{9,10}.

Here, we focus on revealing one major limitation to the input data for widely used biodiversity metrics and suggest improvements needed to support their use in decisions to screen for and prioritize global-scale investment in conservation actions. These decisions include, for example, strategies by global conservation organizations wanting to identify, protect and retain areas of significant biodiversity value (e.g.¹¹), or by companies with global assets or supply chains aiming to reduce their footprint on biodiversity¹². In both contexts, primary field data is ultimately needed to validate decisions on where and how to develop and implement mitigation and conservation actions. However, the first step – screening for good candidate sites – typically involves the use of global biodiversity indicators and metrics¹³. Hundreds of these metrics exist⁹, many of which are computed from secondary data and often include at least one land cover map as a proxy for land use pressures on the state of biodiversity (Table 1).

¹The Biodiversity Consultancy, Cambridge, UK. ²Centre for Biodiversity and Conservation Science, University of Queensland, Brisbane, Australia. ³School of the Environment, University of Queensland, Brisbane, Australia. ⁴University of Cambridge, Cambridge, UK. ⁵Institute for Ecological Economics, Vienna University of Economics and Business, Vienna, Austria. ⁶Advancing Systems Analysis, Novel Data Ecosystems for Sustainability Group, International Institute for Applied Systems Analysis, Laxenburg, Austria. ✉email: laura.sonter@thebiodiversityconsultancy.com

Biodiversity	Type	References	Land cover products			
metrics			(ESA,	(Friedl & Sulla-Menashe,	CGLS	
			2020)	2022)	2019	
			300m	UMD 2022	IGBP 2022	100m
				500m	500m	
Mean Species	Pressure	[20]	#			
Abundance	– state					
(MSA) – GLOBIO						
Biodiversity	Pressure	[34]		#	# –	
Intactness Index	– state			[38]	[39]	
(BII)						
Species threat	Pressure	[35]	#			
abatement and	– state					
restoration						
(STAR)						
Forest	Pressure	[36]				
Landscape						
Integrity Index						
(FLII)						
Natural Lands	Pressure	[23]	+	+		
map v0.3						
Area of Habitat	State	[37]				
maps – used to						
identify Key						
Biodiversity						

Table 1. Selection of global biodiversity metrics reliant on analyzed land cover datasets, either as direct inputs (shown in dark green) or as inputs used to develop their direct inputs (shown in light green). Refs. [20,23,34–39](#)

Following guidance from the Taskforce on Nature-Related Financial Disclosures, we include metrics that either measure the extent or condition of ecosystems, including pressures as a proxy for condition, and species abundance or extinction risk (TNFD, 2023a). Note, some metrics are reliant on land cover maps from earlier years (#) and/or are of coarser (+) or finer (–) spatial resolutions than the land cover products here.

Global land cover maps, made through remote sensing of the physical Earth surface, including various combinations of vegetation types, soils, exposed rocks, water bodies as well as anthropogenic cover types, such as croplands and built up land, are far from perfect¹⁴. Land cover classification systems are necessarily simple depictions of reality and do not easily translate to land use classes and the pressures these classes have on biodiversity¹⁵. This is particularly true for intensive land uses¹⁶, such as mining, which is a land use likely spread across many classes in global land cover products. This is because mines are small, difficult to systematically detect from satellite imagery¹⁷, include a range of land cover classes, and shift through these classes throughout the mine life.

In some cases, mining land use – i.e. defined here as land cleared, disturbed and converted through mining activities, including mine pits, tailings facilities, and supporting infrastructure – may be classified by global products as a land cover class with similar properties and pressures on biodiversity, such as built up or barren land. However, mines may be classified as a natural land cover class too, either because distinguishing mining land from the surrounding land cover class is not possible due to spectral properties of remotely sensed imagery or due to insufficient spatial resolutions to represent mines, which are irregularly shaped and have high variability in their spatial extent¹⁸. Indeed, mining land expansion happens at different spatial and temporal resolutions to those of other anthropogenic land cover classes that do feature in classification systems, like agriculture¹⁹.

Using land cover maps to indicate mining pressures on biodiversity may have significant implications for computing biodiversity metrics^{20,21}, influencing and bias decisions on where and how to mitigate land use pressures on biodiversity. If mining land intersects with an anthropogenic land cover class with similarly large pressures to biodiversity (e.g. urban environments), the absolute and relative errors in computed biodiversity metrics may be insignificant. But, if mining land intersects with a land cover class containing natural vegetation conditions and inferred to contain similar biodiversity (in terms of composition, structure and function) to sites without human pressure, current metrics may greatly overestimate biodiversity and thus underestimate opportunities to improve it. The extent of these limitations is currently unknown but are likely evident in metrics being developed for broadscale use by the private sector, such as the Science Based Targets Network^{22,23}.

The consequences for biodiversity conservation could also be significant, given that mining often occurs in biodiverse areas^{24,25} and can completely remove it for long periods of time²⁶. The significance of these limitations is likely to increase as demand for mined materials grows in response to multiple drivers²⁷, including delivery of global sustainable development goals²⁸, while corporate commitments to mitigate impacts are also emerging²⁹. However, the consequences of assuming land cover products can estimate mining pressures on biodiversity may also differ regionally, given that mining threats to biodiversity differ depending on where and how mining occurs and what land cover classes are dominant in the surrounding landscape.

Therefore, the goal of this study was to reveal potential limitations of using global land cover datasets in assessing mining pressures to biodiversity, focusing on those that could be used by global mining companies and organizations dependent on mined commodities to screen opportunities to mitigate impacts and improve biodiversity in areas affected by mining. We answered three questions:

1. How do global land cover maps used to compute widely-used biodiversity metrics classify land used for mining?
2. Does the proportion of mining land classified as a natural land cover class differ among (a) land cover products, (b) mining land products, and (c) geographical regions?
3. Which factors explain why mining land is classified as a natural land cover class, and what proportion of these areas could be addressed by either using more recent and higher resolution land cover maps, or through alternative methods to mapping pressures to biodiversity?

Methods

We use two recently published global maps of mining land use, which we refer to as Maus et al.¹⁷ and Tang and Werner³⁰ polygons. These datasets vary in their approach to mapping mining land and thus their global extent and distributions differ³⁰. Notably, Maus et al. polygons use a more inclusive definition of mining land use, as mapped polygons sometimes include unaffected land that occurs in between mining infrastructure, when compared to Tang & Werner polygons, which depict individual components of mines (e.g., waste rock dumps, mining pits) and exclude land between. In combination, these datasets identify 120,000 km² of mining land cover, with some overlap and gaps between the two (Tang & Werner: 65,588 km²; Maus et al.: 101,524 km²). A comprehensive analysis of geospatial differences and similarities between these two products is provided by³⁰.

We used these mining polygons separately to clip four global land cover products used to compute a range of biodiversity metrics (Table 1). These land cover products included one produced by the European Space Agency (ESA, 2020; 300 m³¹), one by the Copernicus Land Monitoring Services (CGLS 2019; 100 m³²) and two by the U.S. Geological Survey (USGS) and National Aeronautics and Space Administration (NASA)³³, of which one was derived using the International Geosphere-Biosphere Program classification scheme (IGBP, 2022, 500 m) and one using the University of Maryland classification scheme (UMD, 2022, 500 m). Preserving the original spatial resolution and classification scheme of each product and using the most recent year available (see Table S1), we summarized the area and proportion of land cover classes within investigated mining polygons.

We used ArcGIS Pro's "Tabulate Area" tool to ensure all pixels overlaid by the mining polygons were included in our analysis. This approach accounted for partial pixel contributions, addressing potential bias from undercounting pixels that did not have their centers within the polygons. To address potential over/undercounting, we implemented an area-weighting correction by calculating the proportion of each pixel intersecting the mining polygon and adjusting the area calculated accordingly. This method minimized bias by capturing both the additional area from pixels extending beyond the polygon boundaries and the gaps where polygons were not fully covered by entire pixels. We present the differences between raw and weighted areas in Supplementary

Information 2, which shows the weighting reduced the total area but did not affect the proportion of polygons classified as a natural land cover class.

We also reclassified their original land cover classes into three broader classes (natural, anthropogenic, and water; see Fig. 1) to test the hypothesis that mining was more often classified as anthropogenic land cover classes than natural cover classes. We compared the area and proportion of land within mining polygons classified as natural vs. anthropogenic among mining datasets (Maus et al. and Tang & Werner), land cover products (ESA, UMD, IGBP, CGLS), and continents. We repeated these analyses by excluding mining polygons that were smaller than two-pixel sizes of the land cover datasets to test the sensitivity of our results to differences in their spatial characteristics. Figure S5 shows the distribution of mining polygons among size classes.

To determine the factors potentially explaining why mining polygons were classified as natural, we visually inspected the mining polygon product that yielded the lowest proportion of natural land cover (i.e., Tang & Werner polygons). For each land cover dataset, we randomly sampled 650 points from the natural land cover classes within mining polygons. We stratified sample points geographically, by the number of mining polygons per continent, and limited points to one per mining polygon. We visually inspected each sampled error point, using high resolution Sentinel (2017) and Google Earth (2020) imagery, to determine one of four possible explanations for natural land occurring within mining polygons: (1) temporal mismatches, (2) insufficient spatial resolution, (3) land cover classification errors, and (4) natural land occurring within mining polygons. Further detail on visual inspection is found in the caption of Table S2.

Results

More than half of the area of land within mining polygons was classified as natural (56–77%; 36,652–77,905 km²) and only 22–40% was classified as an anthropogenic cover class, although results varied among combinations of datasets (Fig. 1, Fig S1). A greater proportion of Tang and Werner polygons was classified as anthropogenic (27–40%) than Maus et al. polygons (22–34%), although Maus et al. polygons identified a greater absolute area of anthropogenic land within polygons globally (Fig. 1, Fig S1). We found a greater proportion of land was classified as anthropogenic when using the ESA land cover product (34–40%, Fig. 1) compared to UMD, IGBP and CGLS (22–29%, Fig S1). For Tang & Werner polygons, we also found that when land was classified as natural, ESA (2020) most often detected shrubland dominated classes, whereas UMD (2022) and IGBP (2022) most often detected grassland classes (Fig. 1, Fig S1). Excluding small polygons (i.e., less than 2 pixels of the land cover maps analysed) only reduced the proportion of mining polygons that were classified as natural for the Tang & Werner – UMD (2022) combination, which declined from 72.0 to 71.9% (Fig S2).

The proportion of land within mining polygons classified as natural varied geographically. Using Tang & Werner polygons and ESA (the combination with the least amount of natural land within mining), the proportion of natural land ranged from 46% in Europe to 69% in Australia (Fig. 2A). The ESA land cover product had the lowest proportion of natural land in all regions (Fig. 2A), except for South America, where the proportion of natural land cover was lower for UMD, IGBP and CGLS land cover products (Fig S3). Globally, half of the mining land classified as natural occurred within Asia, due to the relatively large extent of mining polygons occurring within this continent (Fig. 2A). We found natural land within mining polygons included a range

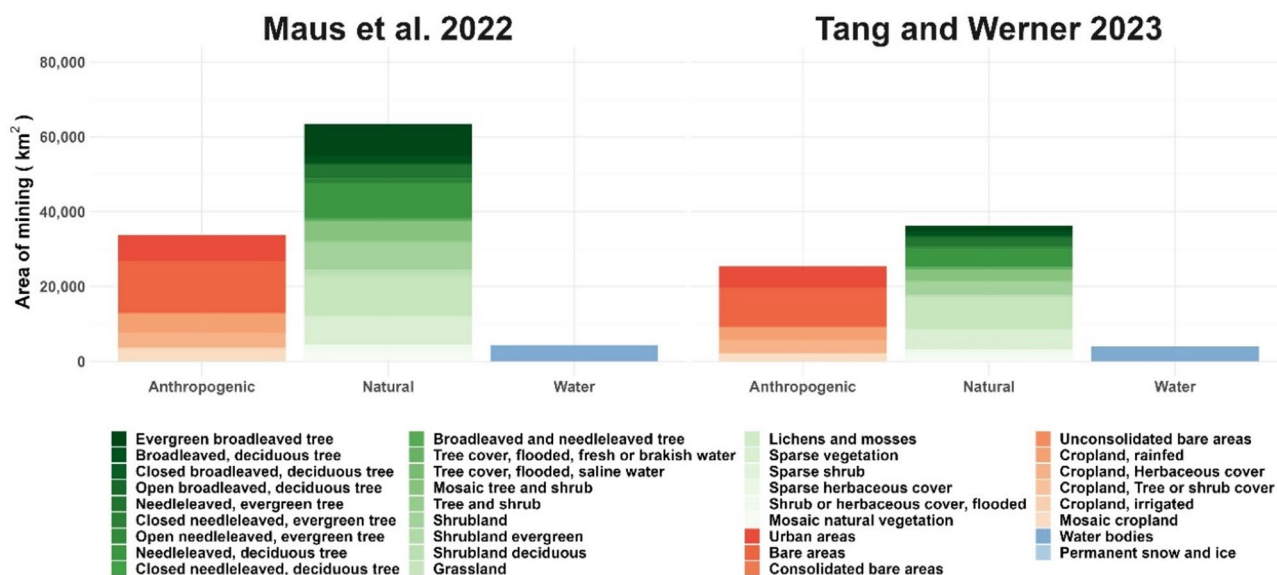


Fig. 1. Land cover within mining polygons (Maus et al. left; Tang & Werner right), as classified by ESA 2020 land cover product. Detailed land cover classes are those originally classified by the land cover product; broader classes were classified for use in this study (i.e., Anthropogenic, Natural and Water). Fig S1A–C show equivalent graphs for other land cover products (UMD, IGBP, CGLS). Fig S2 shows the sensitivity of the analysis to removing small mining polygons.

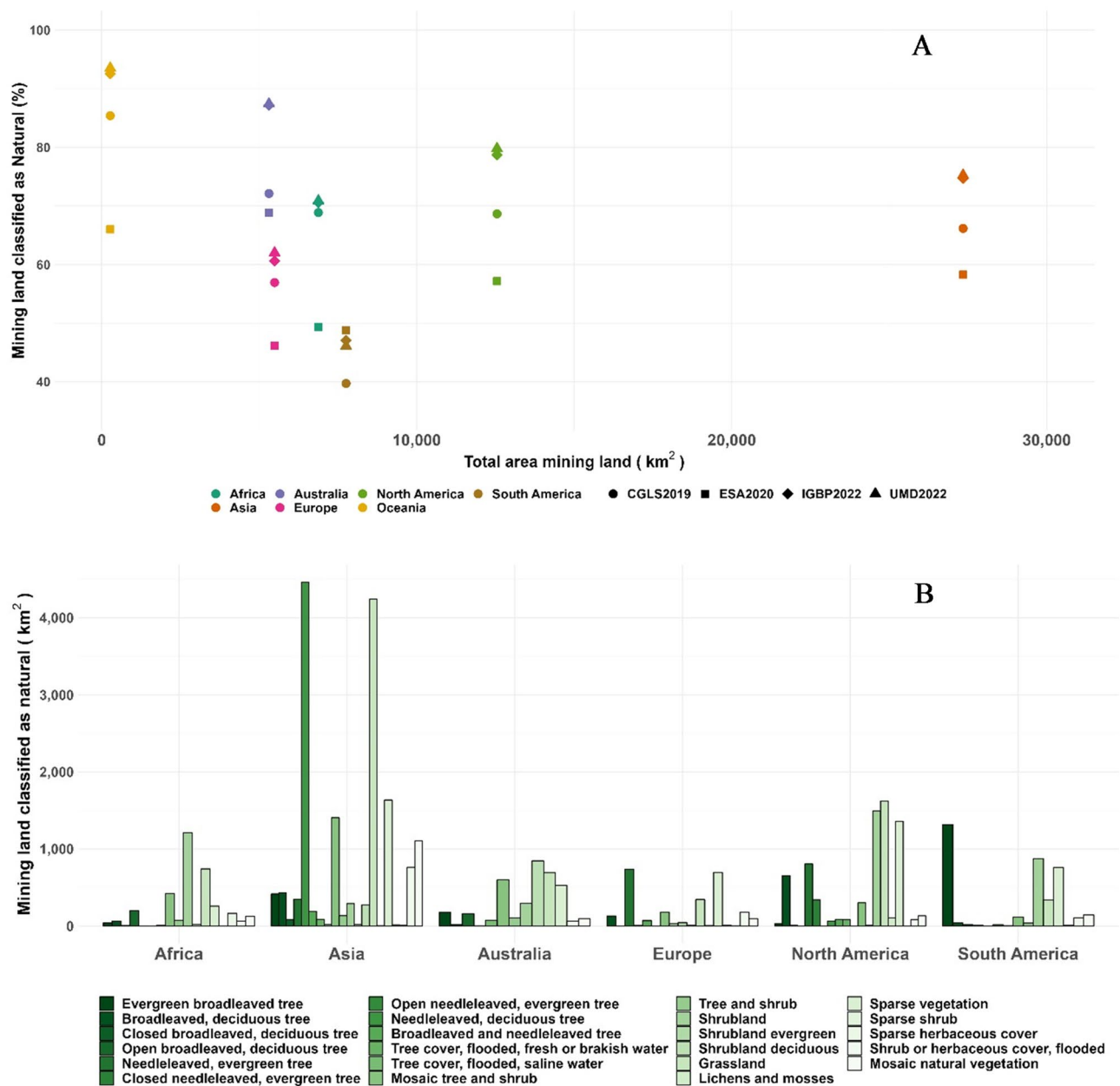


Fig. 2. Percent of land within mining polygons classified as natural land cover (Tang & Werner data). **(A)** (top) shows the relationship between misclassification errors (y axis) and the total land area of mining polygons (x axis) per continent for ESA, IBGP, UMD and CGLS land cover products. **(B)** (bottom) shows misclassification errors distribution among ESA land cover classes. Fig S3A shows the equivalent graph for Maus et al. data. Fig S3B shows the equivalent set of graphs when using all other combinations of mining polygons and land cover products.

of original cover classes, with tree dominated classes the largest class in most regions except for Australia and Africa, where the largest class is shrublands (Fig. 2B).

We found evidence of all four factors explaining why mining land was classified as natural (Fig. 3, Table S2, Fig S4). However, by far the dominant factor (>80% for all land cover products) was due to land cover classification systems being unable to distinguish mines within natural land cover classes (Fig S1). For Tang & Werner and ESA, 5% of our samples were due to mining polygons including some natural land cover classes, 2% were due to there being no mine visible in the validation data, and 0.8% were due to temporal mismatches, where the mine was younger than the land cover product. We found 11% of mines classified as natural classes were due to spatial mismatches between datasets (when the mine was smaller than one pixel) and the use of higher resolution land cover product (CGLS at 100 m resolution) reduced this value to 3%. The greater proportion of natural land within mining polygons found in South America were due to spatial mismatches (i.e., 22% where

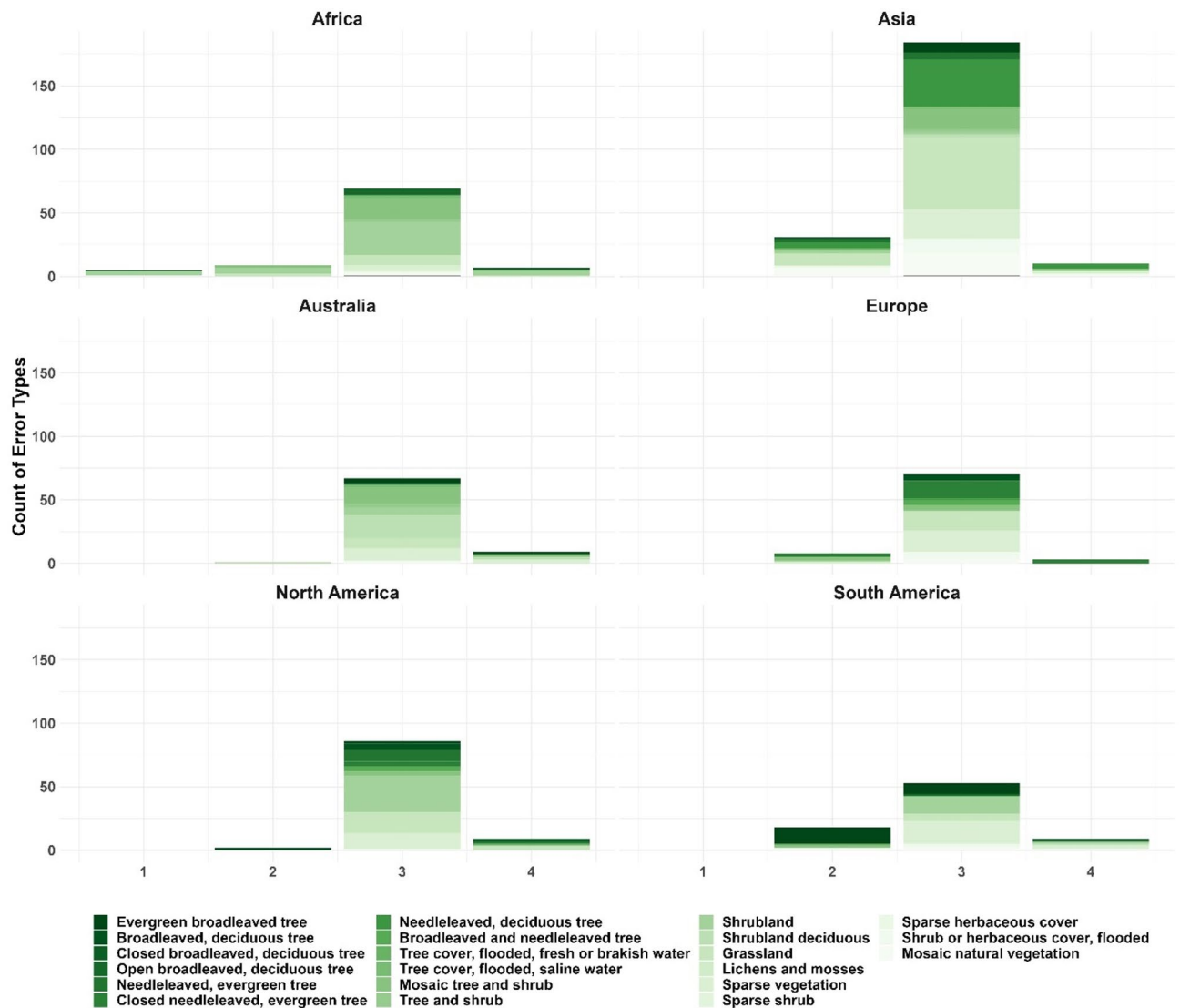


Fig. 3. Factors explaining natural land within mining polygons (Tang & Werner mining polygons; ESA land cover product). Five factors included: 1. temporal mismatches in mining and land cover datasets; 2. insufficient spatial resolution to detect mining land cover; 3. land cover classification unable to distinguish mines from natural land; and 4: mining polygons contained some natural land. Counts of errors were obtained by visual inspection of higher resolution imager at 650 random points, which were spatially stratified by continents depending on their land area of mining polygons (Africa: 90; Asia: 225; Australia: 77; Europe: 81; North America: 97; South America: 80). Equivalent graphs for other land cover products (UMD, IGBP and CGLS) are shown in Fig S4.

mines were smaller than the ESA product; Fig. 3). Spatial mismatches were also more frequent globally when using UMD (17%) and IGBP (24%) land cover products (Fig S4).

Discussion

Global land cover maps are used as inputs to the indicators and metrics informing major risks and opportunities for biodiversity conservation, including those recommended by the Monitoring Framework for the Kunming-Montreal Global Biodiversity Framework⁴⁰ and the Taskforce on Nature-Related Financial Disclosures⁴¹. However, our results reveal a major source of bias in assuming that land cover can be used as a proxy for mining land use pressures on biodiversity. We found that more than half of global mining land use is currently classified as a natural land cover class, suggesting the biodiversity within these regions is under pressure²⁶. Here, we explain how and why these results translate to biases in biodiversity metrics, describe the decisions they are likely to influence, and list key improvements needed to map global mining land use pressures to inform biodiversity mitigation and conservation action in mineral-rich regions. While primary field data must inform and validate any on-ground conservation actions, comprehensive field data is scarce for much of the planet⁴² and practical

solutions are needed now to ensure the robust use of global land cover datasets, which were never intended to be used as proxies for land use pressures to biodiversity.

Anthropogenic and natural land cover within mining polygons

At least 120,000 km² of the terrestrial land surface area is classified as used for mining by the two major mining land use products⁴³, much of which occurs in biodiverse areas of conservation significance^{24,44,45}. To date, global land cover maps have understandably not included an explicit cover class that would capture mining activities, given that mining is a land use, not a land cover type. Given the diversity of land cover types that constitute “mining” – e.g. mining pits, waste rock dumps, processing and supporting infrastructure, and mined land rehabilitation and closure sites⁴⁶ – it is unsurprising to detect a range of anthropogenic cover classes within these polygons (Fig. 1; Fig S1). These included urban and built-up or bare land, while these broad classes do correspond to prior knowledge of land cover possibilities within mining sites, there are instances in which these classes may not accurately capture mining land use pressures to biodiversity. Such might be the case for bare land (i.e. the dominant individual class found within mining polygons for ESA), which in a mining context, can also cause large changes in topography (i.e. deep mine voids; mountaintop removal) that are structurally and functionally distinct from relatively flat bare land used as haul-truck roads⁴⁷.

Similarly, natural land cover classes found within mining polygons spanned many vegetation classes depicted by land cover maps (Fig. 1; Fig S1). Some mining polygons did contain natural or ‘natural looking’ vegetation (Fig. 3) and this explanation may be true if sites include rehabilitation of mined land or patches of remnant vegetation. The biodiversity of these sites, however, likely remains under pressure due to mining operations, including dust, noise, tailings and the risks of contamination or mine waste spills^{26,48}. Our evaluation of natural land cover within mining polygons suggested that most natural land within mining polygons was caused by an omission in global land cover classifications or an inability to distinguish mined areas and infrastructure from natural cover classes, particularly systems dominated by shrublands, grasslands and mixed and mosaic vegetation classes. This is likely due to their similar spectral characteristics to mined land and contribute to the relatively lower overall accuracy of these classes (49% user accuracy for grasslands; <40% for mixed and mosaic vegetation classes; ESA).

Implications for using biodiversity metrics for conservation action

Land cover classes that contain vegetation is likely of better ecological condition than anthropogenic classes and, as a result, classifying mining as natural systematically overestimates the biodiversity that land contains^{20,34}. Similarly, metrics that overestimate biodiversity also underestimate opportunities to improve it, either through conservation or mitigation actions. While the global significance of these errors on total estimates of biodiversity may be relatively small, since mining occupies less than 1% of terrestrial land¹⁷, they could have pronounced effects on some biodiversity features that co-occur with mineral resources²⁶, such as those ecosystems classified as natural but significantly degraded by mining in Brazil’s endangered Rupestrian grasslands or Madagascar’s littoral forests^{49,50} (Fig S5). Further, given that mining has been linked to land with disproportionately high levels of species richness, endemism, or conservation significance^{25,44,51}, global overestimates in biodiversity condition caused by omitting mining from land cover products may be larger than indicated by the extent of natural land within mining land area alone.

Errors in biodiversity metrics yield different risks depending on how and by whom they are used. For example, a global mining company may use metrics to screen their portfolio, identify assets occurring in locations with significant biodiversity value and thus risks to it, and prioritize target setting, impact mitigation, and conservation action at these high risk sites. Our results suggest that biodiversity is likely overestimated at many of these sites, potentially leading to a waste of resources in following up with local studies where biodiversity risks are low. Some regions had larger proportions of mining land classified as natural (Fig. 2A), which may further incorrectly bias prioritization towards assets in countries with either more mining land classified as natural (e.g. Asia; Fig. 2A) or larger proportions classified as natural (e.g. Australia and Oceania; Fig. 2A). A more problematic scenario may occur when metrics are used to assess average global mining impacts to biodiversity for use by companies with minerals in their supply chains. This is done through the application of life cycle assessment tools and is necessary when the location of assets causing impacts are unknown⁵². Not only are there potentially impacts in the underlying data used for averaging, but the values are highly dependent on which sites they are taken from. Much more transparency is needed around both mineral supply chains and the methods used to calculate average biodiversity risks.

Opportunities to address the resultant bias in biodiversity metrics

Several options exist to overcome, or at least better understand, the bias that exists in using land cover products to infer mining land use pressures. For producers and users of existing biodiversity metrics, we recommend understanding the limitations of their land cover products when mining is of relevance to the decision context, selecting those most capable of detecting it as an anthropogenic class. For example, we found ESA more often classified mining polygons as anthropogenic (Fig. 1), on all continents except South America, where UMD and IGBP were better when using Tang and Werner polygons (Fig. 2A). Relying on land cover products with higher spatial resolution might also help. However, biases often caused by spatial mismatches – the second highest category (Fig. 3) – may be an underestimate given the decision rules used in global land cover products that only detect land cover changes at a 1 km resolution (ESA, 2020). This was particularly true in Asia, South America, and Africa, possibly related to artisanal small-scale mining being a prevalent driver of mining and such polygons were smaller (global geometric mean: 0.12 km²³⁰).

Steps can also be taken to compute new global datasets that combine mining land use with global land cover products, and to recalculate biodiversity metrics where relevant. Land cover products could make use

of mining polygons as training data to integrate a mining class into global classification schemes. This could help address many mining areas not currently included by manual mapping efforts made to date⁴³, including many non-metal commodities, such as sand and construction materials²⁵. Opportunities also exist to model land cover footprints using information on historic mine land use and production data⁴⁶. However, an easy first step would involve combining existing land cover and mining products, carefully choosing the mining polygons best suited to the decision context. For example, Tang & Werner polygons would more accurately capture direct mining land use pressures on biodiversity, which may be valuable in calibrating pressure-state for computing biodiversity metrics. Whereas Maus et al. polygons provide a more conservative picture of where pressures may exist and thus be more suitable for screening, as was originally proposed as per the Science Based Targets Network method for mapping Natural Lands²³.

Another way to improve derived biodiversity metrics is to utilize cumulative impact mapping methodologies, which combine satellite derived land cover data with curated 'bottom-up' products of anthropogenic influence, including human population density, built infrastructure and roads⁵³. These products have been created to overcome issues that land cover classifications ignore many forms of industrial influences that are hard to derive from satellite images⁵⁴. Beyond mapping the amount of human industrial influence on the planet⁵⁵, these methodologies are increasingly used to highlight biodiversity risk^{56,57} but are rarely used in global biodiversity metrics (but see⁵⁸). A future research priority would be test the utility of these cumulative impact mapping products in contemporary biodiversity metrics and to see if they are better at capturing mining (when compared to land cover products). A second research priority is to establish ways to ensure mining data is imbedded within cumulative impact assessments (a current limitation to many global industrial influence maps, e.g.⁵⁹), including ways to score the varying pressures mining have on landscapes⁶⁰.

Future research and data needs

Our research highlights the need of more targeted ecological field studies, particularly in regions with large mining sectors and significant biodiversity value but where there is desperate shortage of ecological data. Doing this upfront should be seen as a strategic investment by governments and industry in areas with significant mineral resource potential. Ensuring local data collection and information disclosures to a global repository would build knowledge and capacity to address mining pressures to biodiversity. This could include much needed improvements of mining into existing platforms, such as the IUCN's Red List of Threatened Species⁶¹. However, this knowledge must also capture other mining pressures, that are not captured by land cover products or may not fall within the responsibility of mining companies. This includes mining as an indirect driver of land use pressures on biodiversity, for example due to regional infrastructure requirements^{60,62} and non-land based pressures on biodiversity, such as water withdrawals and pollution¹⁸. This will require land cover maps to be integrated with other geographical information pre- and post- screening for biodiversity risks and conservation opportunities.

While this research is being generated, we believe companies and other decision making bodies (including national governments and the finance sector) assessing impacts of mining on biodiversity, or opportunities to improve it, within direct operations or supply chains, should be aware that the state of nature – for biodiversity, as indicated in this study, but potentially also for other environmental factors modelled using land cover data, such as carbon storage and water quality – provided by global metrics is likely overestimated, and additional effort is required for validation.

Data availability

The datasets analysed during the current study are publicly available and accessible via the following links: <https://zenodo.org/records/3938963>, maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf, <https://doi.org/10.5067/MODIS/MCD12Q1.061>, <https://doi.org/10.1038/s41597-022-01547-4>, <https://doi.org/10.1038/s43247-023-00805-6>.

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Author contributions

L.J.S. wrote the main manuscript text and I.N. conducted analyses and prepared all figures. All authors contributed to conceptualisation of the study and reviewed the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

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Correspondence and requests for materials should be addressed to L.J.S.

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